Beyond the Visual System: A Cognitive Model of Color Categorization and its Application to Color Image Quality

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Abstract

The paper presents a cognitive model of color categorization and discusses its applications to color image quality. The structure of color categories is argued to resemble the structure of the distribution of colors in the perceived world. This distribution can be represented as color statistics in some perceptual and approximately uniform color space (e.g., the CIELUV color space). The process of color categorization can be modeled through the grouping of color statistics by clustering algorithms (e.g., K-means). This model explains the location, and rank of color categories. The model might be considered as a first step towards developing a uniform cognitive color space. The equality of distances between color categories can be the criterion of uniformity for such a space. It is argued that some image processing techniques (e.g., gamut mapping, color quantization, segmentation, coding etc.) might be more appropriate to perform in a cognitively uniform color space.

Introduction

Most of modern image quality metrics are based on the properties of the visual system only, and do not take into account cognitive aspects involved in image quality judgements. Such metrics can be very useful to define the subjective tolerance to reproduction errors or artifacts, especially at the threshold level. They can provide the answer on the question 'what do people *accept* to see in images'. However, they are unable to respond on more general questions of the supra-threshold level 'what do people *expect* to see' or 'what do people *prefer* to see' in observed pictures. To answer these questions, one has to consider high-level cognitive phenomena such as memory and preference.

The phenomena of memory and preference have been studied extensively in color science. Several experiments revealed a discrepancy between memory colors, preferred colors, and actual colors for various objects.[1-5] There was evidence of a significant increase in saturation of memory colors for some object categories (e.g., grass, sky, and food items). However, other categories showed no such shift (e.g. sand, skin), or showed it in the opposite direction (e.g. concrete). To explain these results, Newhall et al.[2] have proposed that the color shift in memory and preference judgements was caused by the influence of prototypical object colors. Recently, Yendrikhovskij et al.[6] have developed a computational model of prototypical object colors, which was used to analyze perceived naturalness[7] and quality[8] of color images.

Prototypes, or the most typical examples of object categories, are presumably developed through the process of generalization from the population of apparent object seen in the past. The Generalization Theory proposed by Shepard[9] provides an explicit explanation for generalization principles that govern the organism's behavior. The process of generalization is closely related to another cognitive process, the process of categorization. The General Recognition Theory,[10] which is one of the most advanced categorization models, demonstrated that the structure of natural categories could be effectively modeled by a multivariate normal (Gaussian) distribution. This paper shortly describes a computational model of color categorization (CMCC) that adopts the Generalization Theory and General Recognition Theory. For a complete description, see Ref. 11. The paper also discusses possible applications of this model for color imaging science.

Color Categorization

Definition of Color Categorization

Color categorization can be defined as the grouping of color sensations into classes "by means of which nonidentical stimuli can be treated as equivalent".[12] In general, this grouping has can be performed at different levels of visuo-cognitive processing. A model described in this chapter focuses on the semantic color categorization (i.e., color naming), which takes place between perceptual and semantic levels. More specifically, the model considers single-word color names, so-called "basic color terms", originally defined by Berlin and Kay,[13] and extensively studied by Boynton and Olson.[14]

Origin of Color Categorization

The idea about external (ecological) origin of color categorization was discussed at great length by Shepard,[15] who proposed that this organization most likely reflects something about natural groupings of the surface reflection distributions of biologically significant objects or something about the way in which terrestrial lighting has typically varied during evolutionary history. The information about surface reflections and terrestrial lighting is available to observers only through the process of color perception. As a result, the categorical color organization was argued to have an internal (physiological) basis and have originated from metrical properties (e.g., interpoint distances) of the perceptual color space.[16]

One of the main assumptions advocated in this paper is that the structure of color categories originates from the statistical structure of the perceived color environment that was observed throughout an individual's life. By the use of words (1) 'perceived' and (2) 'environment' this assumption recognizes that color categorization is determined both by (1) the internal properties of the sensorial system and (2) the external properties of the outside world. From this perspective, color categories of an individual *A*, for example, might be different from ones of an individual *B* because of differences in their visual receptors (e.g., the individual *A* is a normal trichromate; individual *B* is a dichromate) or/and due to differences in their environments (e.g., the individual *A* lives in the Northeast part of Canada; individual *B* lives in the Southwest part of the US).

Model of Color Categorization

This section provides a description of a computational color categorization (CCC) model. The CCC model consists of five major components: physical environment, color perception, perceived color environment, color categorization, and color category system.

Physical color environment corresponds to physical characteristics of visual stimuli seen by an individual in the past. A visual stimulus defines a momentary pattern of light reflected/radiated by observed objects (e.g., people, trees, fruits, lights, etc.). Generally, the physical color environment can be modeled by a representative sample of color stimuli entered individual's eyes throughout his/her life. Because such modeling is problematic, one has to find plausible alternatives. The CCC model represents the physical color environment by a representative sample of natural (photographic) images.

In line with this idea, a set of 630 natural images was collected. The images were taken from TV net (110 pictures), Photo CDs (170 pictures), and scanned from books about color in nature (350 pictures). They represented typical categories of scenes: portraits, landscapes, flowers, animals, etc. The whole set of natural images contained 5 424 000 pixels. A random sample of 10 000 pixels was chosen for further processing and analysis.

The process of ***color perception*** is modeled as a transformation from a physical domain to perceptually uniform color space. As a suitable approximation the CCC model can choose the *CIE 1976 L*u*v** (*CIELUV* for short) color space, because it has an associated perceptually uniform chromaticity diagram. Certainly, other color spaces (e.g., *CIELAB*) and appearance models (e.g., *CIECAM97s*) can be used (see Ref. 17 for a review). The *R*, *G*, *B* gray values representing the sampling of 10 000 randomly chosen pixels were transformed to *r*, *g*, *b* luminance values, then to the *X*, *Y*, *Z* tristimulus values, and eventually, to the *L**, *u**, *v** color coordinates. The transformation into the *CIELUV* color space was made using standard formulas[18] based on the assumption that the images were to be shown on a CRT display with PAL (European color television) standard characteristics.

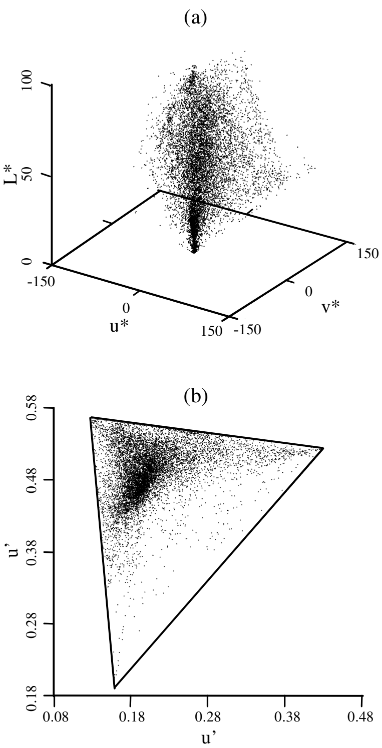

Figure 1. A random sample of the color statistics of 630 natural images in the CIE *(a)* L*u*v* *color space, and (b)* u’v’ *diagram. The solid line indicates the PAL TV color gamut.*

Perceived color environment corresponds to perceptual color characteristics of visual stimuli seen by an individual in the past. Generally, the perceptual color environment can be modeled by statistics of a representative sample of these stimuli in a perceptual color space. The CCC model represents perceived color environment by statistics of the representative sample of the natural images in the *CIELUV* color space.

The sampling of 10 000 randomly chosen pixels representing the whole set of collected images in the *CIELUV* color space is shown in Fig. 1. Apparently, the distribution of the color statistics from the natural images is not spread uniformly in the *CIELUV* color space. Most of the distribution points are concentrated around the lightness (L^*) axis of the *CIELUV* color space. This area represents achromatic colors, i.e., colors close to reference white. Two other areas with a high frequency distribution can be identified in Fig. 1(b). These two areas correspond to red-green and blue parts of the *CIELUV* color space. There are very little colors in the green-blue and red-blue parts of the *CIELUV* color space.

These data agree well with the measurements reported by Howard and Burnidge,[19] Hendley and Hecht,[20] and by Burton and Moorhead.[21] They showed that naturally occurring colors are distributed within a restricted area of the chromaticity diagram, and that there are three important groups of colors in nature. Water, sky, and distant objects fall within a blue region; green plants fall within a yellow-green region; earth and dried vegetation are yellow to orange-red. The last group also includes the average color of human complexions, which have a dominant wavelength close to 590 *nm.*[22]

The process of ***color categorization*** is considered as the grouping of color sensations into classes. Generally, the process of color categorization can be modeled using the concept of vector quantization from information theory. Vector quantization is a data compression method where a set of data points is encoded by a reduced set of reference vectors, the codebook.[23] One can assume that the color categorization is based on the minimum-distance criterion. This implies that points with minimum-distance to each other in the color space are likely to belong to the same color category. Therefore, the process of color categorization can be modeled by a clustering algorithm such as the *K*-means or *ISODATA* clustering algorithms.

The process of color categorization was modeled by *K*-means clustering of the *CIE* $L^*u^*v^*$ color coordinates of the statistics of the natural images in the *CIELUV* color space. Modeling was performed using a *K*-means clustering routine of CANTATA visual programming environment for the Khoros system.[24]. This routine converts an input image into vectors of equal size and performs the *K*-means clustering algorithm on the vectors using randomly chosen *K* initial cluster centers. After *K* initial cluster centers are chosen, the image vectors are iteratively distributed among the *K* cluster domains. New cluster centers are computed from these results, such that the sum of the squared distances from all points in a cluster to the new cluster center is minimized.

Color category system can be described by few basic parameters (location, border, order, number, and weight) of color categories. Generally, these parameters can be modeled by the corresponding parameters (location, border, rank, number, and weight) of clusters derived by the clustering algorithm. This paper describes how the location, and rank of color categories can be computed.

Computing Color Categories

Location of color categories can be computed from coordinates of cluster centers derived by the *K*-means clustering algorithm from the color statistics of the natural images in the *CIELUV* color space. Figure 2 illustrates 11 cluster centers derived by the CANTATA *K*-means clustering algorithm from the sample of 10 000 pixels representing the natural images. The cluster centers are plotted in the *CIE u'v'* chromaticity diagram together with the eleven focal colors found by Boynton and Olson.[14] The original focal colors were derived by Boynton and Olson on the basis of single-word color naming of 424 color samples from the *OSA* space. The coordinates of focal colors shown in Fig. 2 were obtained through the sequential transformation of the *OSA L, j, g,* values to the *CIE Y, x, y* values, and, eventually, to the *CIE* L^*, u^*, v^* values by using standard table and formulae.[18]

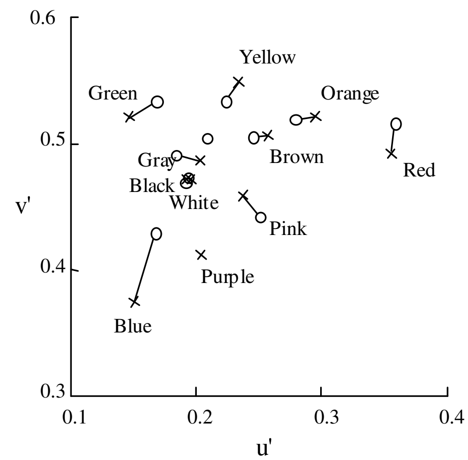

Figure 2. Eleven (circles) cluster centers derived from the color statistics of natural images and (crosses) focal colors found by Boynton and Olson.[14]

The location of the cluster centers in the *CIELUV* space was close to the location of the focal colors with one exception. Among the cluster centers, there was a ‘green-yellow’ cluster, which did not belong to the eleven focal colors described by Boynton and Olson. On the other hand, the analogue of the focal color ‘purple’ was not derived by the *K*-means clustering algorithm.

A linear regression analysis demonstrates that the coordinates of 10 focal colors and 10 corresponding cluster centers are similar: the correlation between their lightness L^* values is r = 0.76 the correlation between their hue H values is r = 0.99; the correlation between their chroma C^* values is r = 0.88; the correlation between their s (saturation) values is r = 0.90. These results support the idea that the structure of color categories originates from the statistical structure of the perceived environment.

Rank of color categories can be computed from the rank (order of emergence) of cluster centers derived by the *K*-means clustering algorithm from the color statistics of the natural images in the *CIELUV* color space.

Berlin and Kay[13] have suggested that if languages are ranked according to number of color category terms, the evolutionary sequence of these terms (in reference to

English names) is generally as follows: (1) black and white; (2) red; (3) green/yellow; (4) yellow/green; (5) blue; (6) brown; (7) pink, purple, orange, and gray. In other words, if a language has only three color terms, they are most likely to correspond to English white, black, and red, and not, for example, to pink, orange, and brown. The exact evolutionary order of color words varies across different languages, but in general shows a remarkable consistency.

The rank of the cluster centers resulting from the *K*-means algorithm is similar to the rank of color terms described by Berlin and Kay. For example, the cluster centers obtained by the *K*-means algorithm with K = 3 roughly correspond to English terms ‘black’, ‘white’, and ‘red’; the cluster centers obtained by the *K*-means algorithm with K = 7 roughly correspond to English terms ‘black’, ‘white’, ‘red’ ‘green’, ‘yellow’, ‘blue’ and ‘brown’; the cluster centers obtained by the *K*-means algorithm with K = 11 roughly correspond to English terms ‘black’, ‘white’, ‘red’ ‘green’, ‘yellow’, ‘blue’, ‘brown’, ‘gray’, ‘orange’, ‘pink’ and ‘green-yellow’.

A moderately high correlation (r = 0.710) was found between rank of 10 color-terms derived from Berlin and Kay’s data and the sum of the two parameters: (1) normalized numbers of items in the clusters and (2) normalized *CIELUV* distance between the cluster center and the average center of all clusters. The results suggest that the development of a color term across languages might be determined by two constraints: (1) frequency at which colors represented by this term occur in environment, and (2) perceived remoteness of these colors from colors represented by already existing terms.

In general, the obtained results support the idea that the evolutionary order of color terms depends on both the external properties of the outside world (frequency of color occurrence) and the internal properties of the perceptual system (metrics of color space). This idea might explain the old mysteries of why the color term ‘red’ has a particular salience in different cultures and why it evolves before other color terms in many languages. The possible explanation is that the color term ‘red’ corresponds to colors that are *both* frequently occurred in the perceived environment of people speaking these languages and substantially distant from other colors in their perceptual spaces. On the one hand, the term ‘red’ evolves before, for example, the term ‘pink’ because pink colors are relatively rare in nature (Fig. 1). On the other hand, the term ‘red’ evolves before, for example, the term ‘green’ because green colors are relatively close to the average center of the all colors in the *CIELUV* color space and, especially, in the *CIE u’v’* chromaticity diagram (Fig. 1).

Applications for Color Imaging

The result of this research can be applied to different areas of imaging science: color quantisation, image quality, gamut mapping, etc. For example, the analysis of the color statistics representing the natural images in the *CIELUV* color space revealed that the obtained distribution was rather uniform in the lightness (L^*) dimension, somewhat nonuniform in the hue (H) dimension, and extremely nonuniform in the chroma (C^*) dimension. Taking into account a roughly inverse relationship between uniformity and redundancy, one can speculate that the color distribution of natural images along the chroma dimension is usually more redundant than along the hue dimension, and much more redundant than along the lightness dimension. Speculating even further, one can hypothesize that quantization along the chroma dimension would probably be less obvious than along the hue and lightness dimensions. Preliminary results have shown that the quantization of the chroma values is, indeed, less noticeable than the quantization of the hue and lightness values. Moreover, the quantization based on the color statistics of the natural images produced a slightly better rendering than the quantization based on the color statistics of the uniform (white noise) image.

The data described in this paper support the assumption that the structure of color categories originates from the statistical structure of the perceived color environment observed throughout individual’s life. Consequently, this implies that the location of prototypical colors in a perceptual space might be different for different individuals. In principle, it is possible to determine the exact coordinates of the prototypical color in the perceptual space for an individual or a group of people (e.g., based on their age, geography, genotype, etc.). This can be achieved, for example, using the method described by Boynton and Olson.[14] If the exact coordinates of the prototypical colors are known, one can create a “prototypical color profile” that is specific for the individual or the group of people. The “prototypical color profile” can be used to customize the process of color reproduction through the transformation of chromaticity coordinates of all colors in an image towards the chromaticity coordinates of the corresponding color prototypes. This transformation can be total (i.e., all colors are replaced by the corresponding color prototypes) or partial (i.e., all colors are shifted towards the corresponding color prototypes). One can hypothesize that an image with colors shifted towards individually specific color prototypes might have a higher subjective image quality than the original image. In general, the concept of the “prototypical color profile” might be used to develop new types of adaptive algorithms that optimize image quality based on individual and cultural differences. This idea needs to be investigated further.

The prototypical colors could also be used to optimize the process of color gamut mapping. In this case, it would be necessary to define a set of prototypical colors produced by a source device (e.g., a CRT monitor) and a set of prototypical colors produced by a destination device (e.g., an inkjet printer). This can be done experimentally by asking observers to estimate prototypicality of colors produced by both devices. When the prototypical colors of the devices are known, they can be used to convert any image from the source device into the destination device in such a way that the prototypical colors of the source device are mapped into the prototypical colors of the destination device. Interestingly, an algorithm that utilizes the notion of categorical colors for gamut mapping has been already proposed.[25]

The possible applications of the concepts of color categorization and color prototypes for color quantization, image quality and gamut mapping might be considered as a first step towards incorporating cognitive aspects of color in imaging science. One can even hypothesize that some image processing techniques (e.g., color quantization, color enhancement, gamut mapping, etc.) might be more appropriate to perform in a cognitively uniform color space rather than in a perceptually uniform color space. The equality of distances between centers of color categories (color prototypes) can be the criterion of uniformity for such a space. The development of a cognitively uniform color space for color imaging science is a subject of future research.

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Biography

Serguei Endrikhovski received a M.S. degree in Psychology from Moscow State University (Russia) in 1994, and a Ph.D. in Visual Perception from the Eindhoven University of Technology (The Netherlands) in 1998. From 1998 to 2000 he was a Research Fellow at the Center for Research on User-System Interaction (Eindhoven, The Netherlands) and a Visiting Research Fellow at the Colour and Imaging Institute (Derby, UK). In his current position at the Eastman Kodak Company Serguei works in a newly emerging area of Image Psychology that studies perceptual, cognitive, and emotional aspects of human experience in relation to images and multimedia.